

# Fully Constrained Least Squares Linear Spectral Mixture Model for Continental Subpixel Land Cover Change Maps

Principal Investigator: Uttam Kumar  
S. Kumar Raja, Cristina Milesi and Ramakrishna R. Nemani

## Objective

To develop and implement a Fully Constrained Least Squares (FCLS) unmixing model for subpixel classification of time series continental Landsat data to study land cover (LC) change and its impact on vegetation, urban growth and carbon sink.

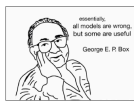
## Why is this research important?

- LC change have important climatic, hydrologic, biophysical, ecologic and socio-economic impacts on the environment.
- Till date, most studies involving LC change adopt per-pixel classification of remote sensing data and largely depend on one time LC thematic map as a base for carbon sink studies.
- Therefore, an automated characterization of large-scale historical changes in LC extent is required to account for the inherent complexity and variability in vegetation dynamics and urban environments.

## Methods

- Unconstrained Least Squares (UCLS), Sum-to-one Constrained Least Squares (SCLS), Normalized SCLS (NSCLS), Non-negative Constrained Least Squares (NCLS), Normalized NCLS (NNCLS), FCLS and Modified FCLS (MFCLS) unmixing models were implemented in C++ programming language with OpenCV package and boost C++ libraries in the NASA Earth Exchange (NEX).
- A set of global endmembers were used to test the algorithms by unmixing computer simulated data, and Landsat data of an agricultural scenario and an urban environment.
- Finally, time series Landsat data of North America from WELD repository are unmixed. The abundance maps in conjunction with DMSP-OLS nighttime lights data are used to extract the urban LC features and analyze their spatio-temporal growth.

### Linear unmixing model



Essentially, all models are wrong, but some are useful.  
George E. P. Box

$$y(x, y) = \sum_{i=1}^n e_i a_i(x, y) + \eta$$

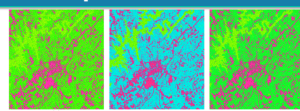
$$y = E\alpha + \eta$$

#### Constraints:

- $a_i \geq 0, \forall i: 1 \leq i \leq N$  Abundance non-negativity constraint (ANC)
- $\sum_{i=1}^N a_i = 1$  Abundance sum-to-one constraint (ASC)

- FCLS extends NNLS algorithm and imposes ASC simultaneously on the abundance values leading to optimal solution.

## Computer simulations



A 6 band computer simulated data: (a) – band 1, (b) – band 4 and (c) – band 6.

- In separate experiments, Gaussian noise with 0 mean and increasing variance of 2, 4, 8, 16, 32, 64, 128 and 256 were added to the data.

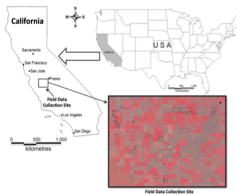
National Aeronautics and Space Administration  
Jet Propulsion Laboratory  
California Institute of Technology  
Pasadena, California

www.nasa.gov

Copyright 2015. All rights reserved.

## Landsat data: an agricultural setup

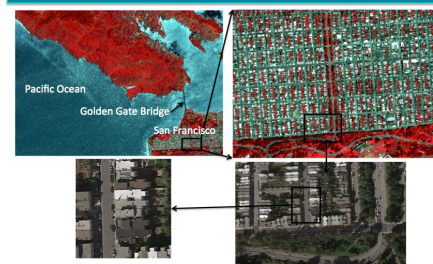
- A spectrally diverse collection of 11 scenes of Level 1 terrain corrected, cloud free Landsat-5 16 bit data calibrated to atmospheric reflectance for Fresno, California, USA were used in this study.
- These data were captured on April 4 and 20, May 22, June 7 and 23, July 9 and 25, August 26, September 11 and 27 and October 13 in the year 2008.



San Joaquin Valley, Central California

Field data collection site in San Joaquin Valley with surveyed boundaries (in black color) from which ground fractional cover were derived for validation are overlaid on a false color composite of Landsat data.

## Landsat data: an urban scenario



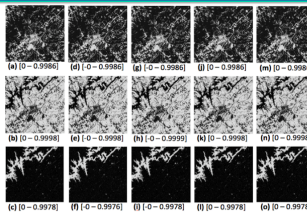
FCC of a part of San Francisco City. Zoomed image of the urban area (marked with rectangles in inset) showing mixing of substrate with vegetation, roads, shadow and dark objects.

## Endmember generation

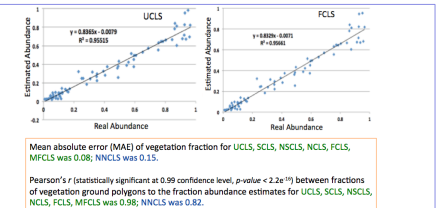
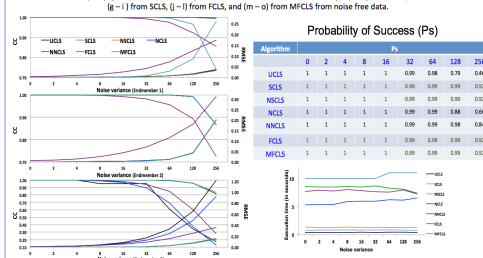
Global mixing spaces were sampled using a spectrally diverse LC and diversity of biomes with 100 Landsat ETM+ scenes to define a standardized spectral endmember of

- Substrate (S) – soils, sediments, rocks, and non-photosynthetic vegetation.
- Vegetation (V) – green photosynthetic plants.
- Dark objects (D) – clear waters, deep shadows, absorptive substrate materials, etc.

## Results

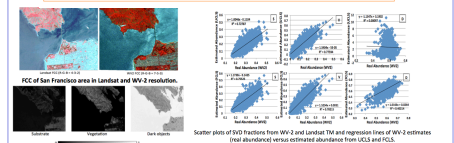


(a - c) synthetic abundance maps for endmember 1-3; (d - f) abundance maps: (d - f) from UCLS, (g - i) from SCLS, (j - l) from FCLS, and (m - o) from MFCLS from noise free data.



Mean absolute error (MAE) of vegetation fraction for UCLS, SCLS, NSCLS, NCLS, FCLS, MFCLS was 0.08; NNCLS was 0.15.

Pearson's  $r$  (statistically significant at 0.99 confidence level,  $p$ -value  $< 2.2e^{-16}$ ) between fractions of vegetation ground polygons to the fraction abundance estimates for UCLS, SCLS, NSCLS, NCLS, FCLS, MFCLS was 0.98; NNCLS was 0.82.



Scatter plots of SCLS fractions from WV-2 and Landsat TM and regression lines of WV-2 estimates (real abundance) versus estimated abundance from UCLS and FCLS.

MAE of S, V, and D fractions for UCLS were 0.11, 0.07 and 0.10; SCLS, NSCLS, FCLS, and MFCLS had MAE of 0.09, 0.05, 0.06 and 0.05; NNCLS and NNCLS had higher values.

Pearson's  $r$  of S, V, and D fractions for UCLS were 0.86, 0.88 and 0.91; SCLS, NSCLS, FCLS, and MFCLS were 0.87 (S), 0.88 (V) and 0.83 (D); NCLS and NNCLS showed lower  $r$  values.

Endmember fractions of S, V, and D from Landsat data (Dark rows) and WV-2 data (second row) from FCLS.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

North America: Substrate-Vegetation-Dark Objects composite of GLS 2010.

## Findings:

- Unconstrained algorithm without ANC and ASC can be used for target detection, discrimination and classification, but not for target quantification.
- FCLS and MFCLS with both ANC and ASC gave more realistic output for abundance estimation with both computer simulated and Landsat data and are suitable for continental / global land cover studies.
- The approach presented here is suitable for the calculation of reliable and consistent physical measures of vegetation and substrate fractions from Landsat data with standardized spectral mixture model.
- Combining substrate fraction with nighttime city lights can be used to isolate the urban areas.
- Vegetation fraction will be used to assess the state of carbon sink at continental levels.



# Characterization of Corrosion Inhibitor Containing Microparticles for Environmentally Friendly Smart Coatings

Benjamin Pearman, PhD

John F. Kennedy Space Center: Corrosion Technology Laboratory

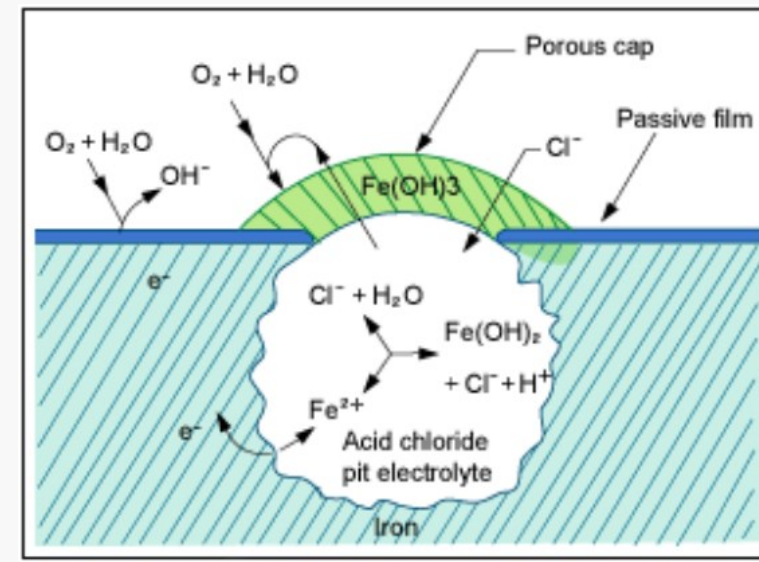
## Corrosion: Everyone's Problem

Metals corrode in presence of oxygen, water & salt

Cost: ~3% of World GDP  $\equiv$  \$2.2 trillion per year

KSC: Most corrosive environment in the world

- Adjacent to Atlantic ocean (salt, humidity)
- Sunshine & heat
- Acidic rocket fumes



### KSC Mission

Sustainable development of a multi-user spaceport for government, military and commercial customers

→ Environmentally friendly corrosion protection system

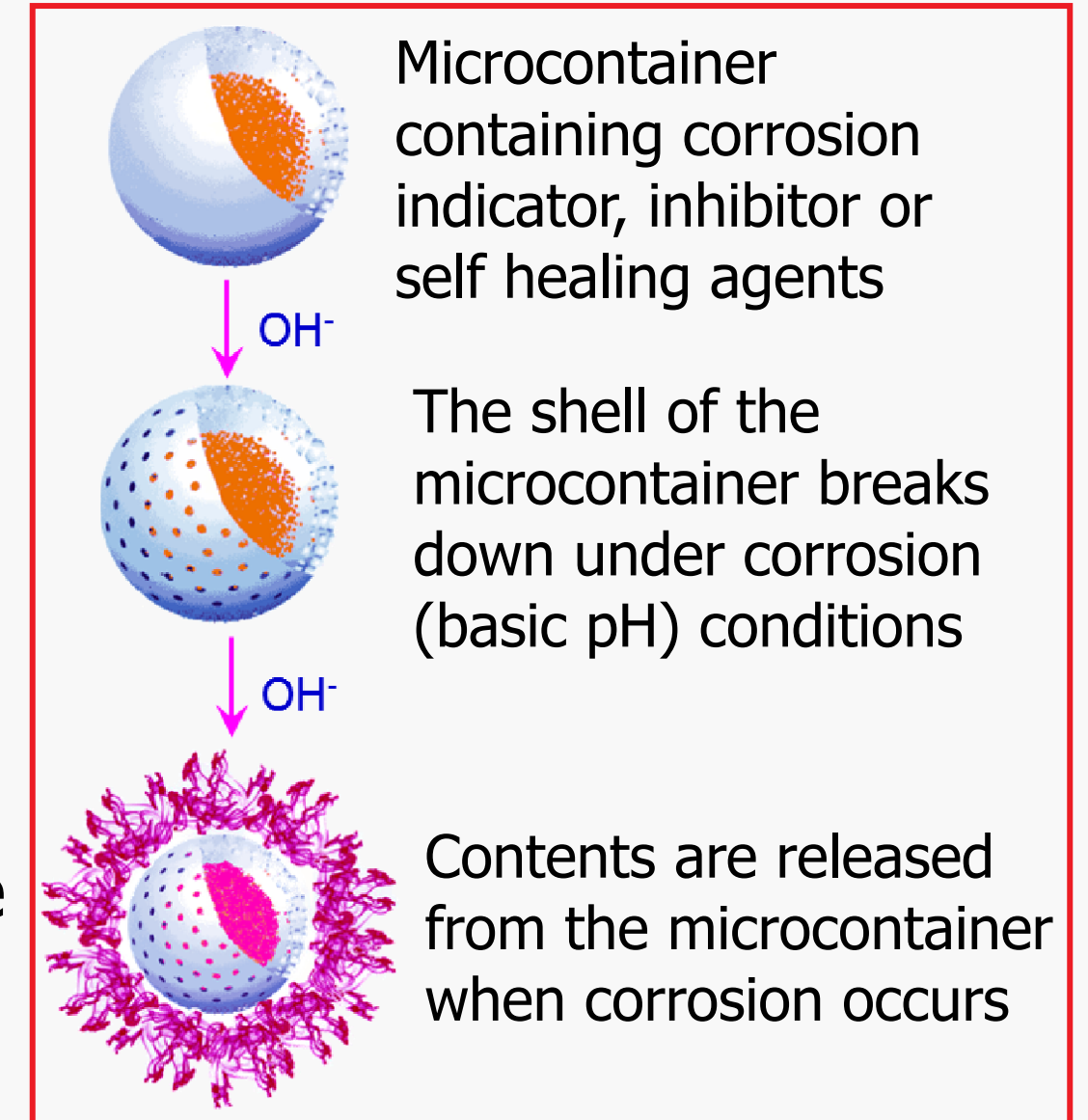
## KSC Corrosion Technology Lab: Problem & Approach

### Problem

Direct replacement of current inhibitors with environmentally friendly alternatives not possible due to coating compatibility and inhibitor solubility issues

### Approach

- Encapsulate inhibitors into coating compatible microcontainers with
- Autonomous, corrosion triggered release
- Characterize release properties and corrosion test performance



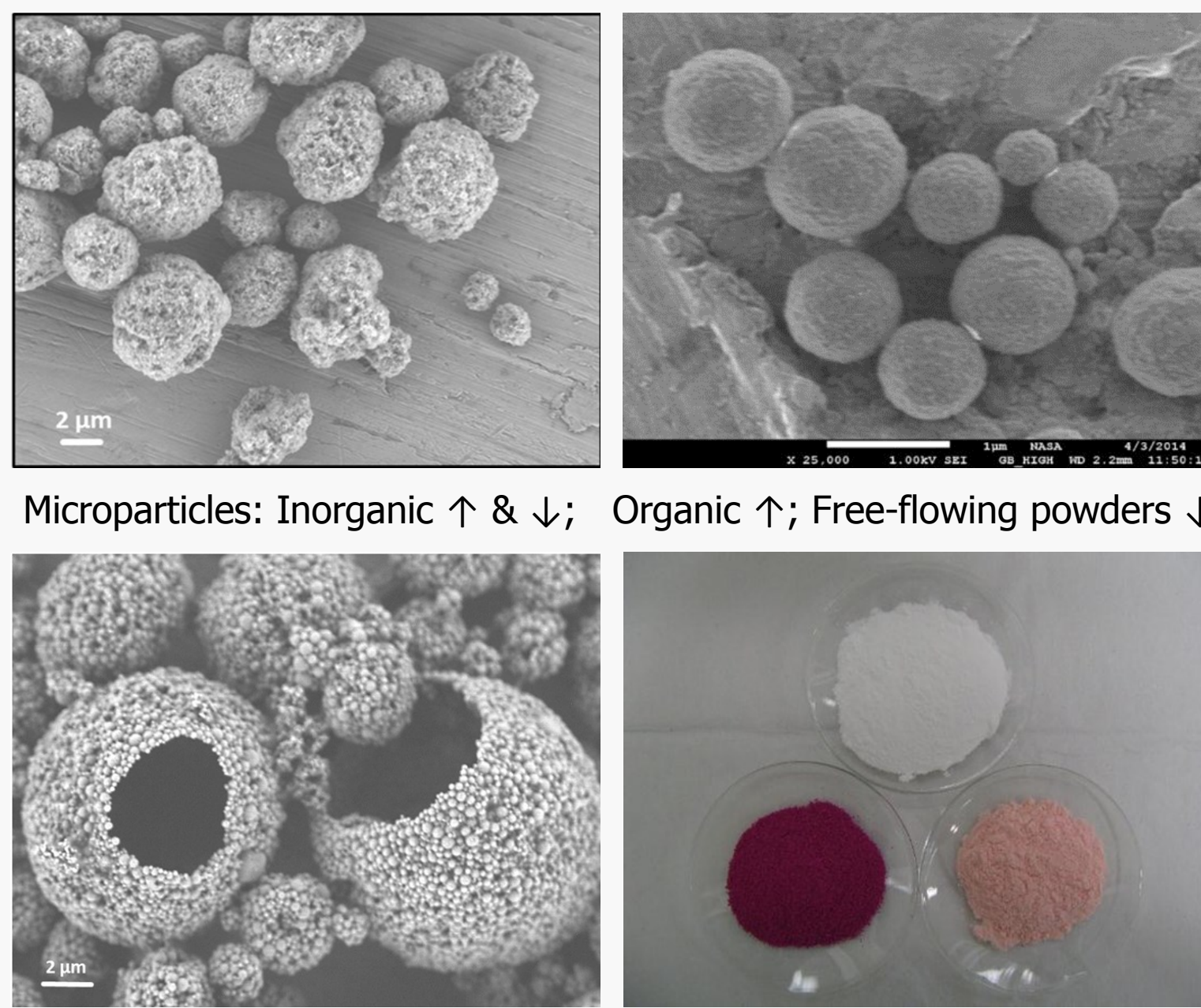
## Encapsulation

Encapsulation of:

- Organic & inorganic inhibitors into
- Organic & inorganic microparticles

Resulting free-flowing powders enable:

- Simple and safe handling
- Incorporation into existing coatings systems



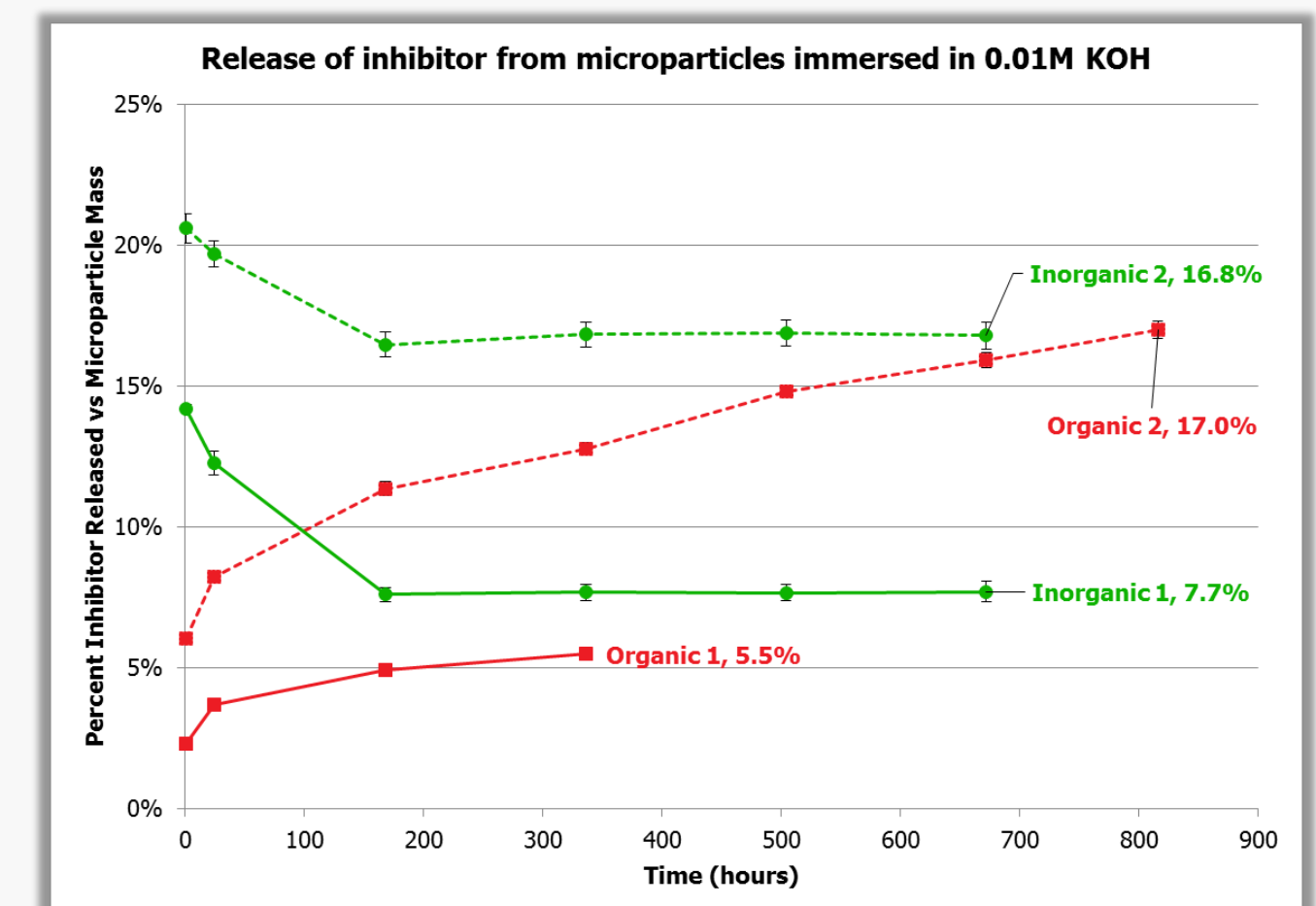
## Inhibitor Release

### Organic Particles

Low initial release  
Long consistent release  
(up to 18 weeks)

### Inorganic Particles

High initial release  
Absorption properties

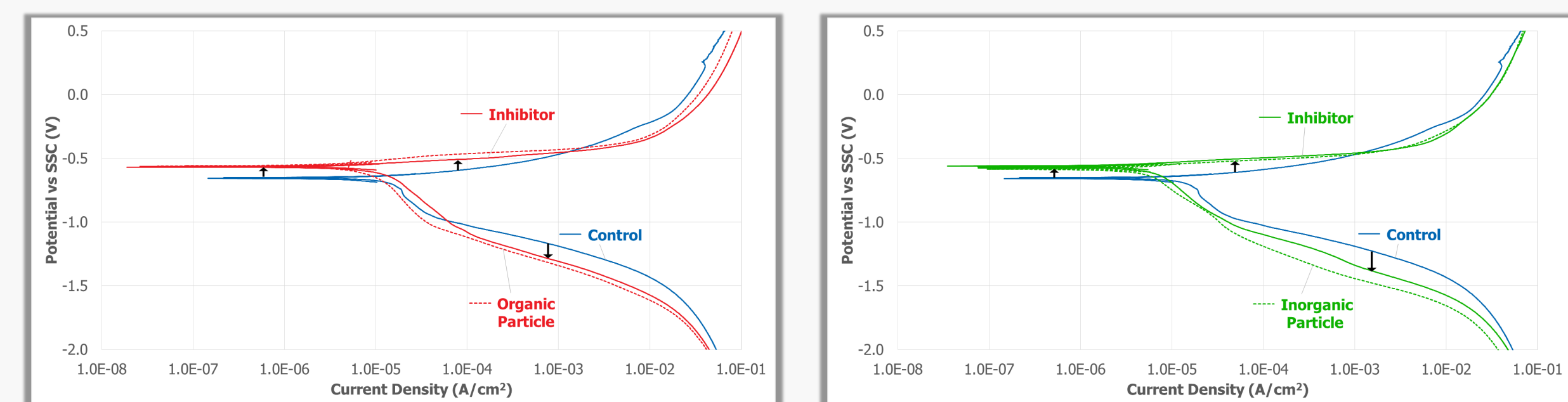
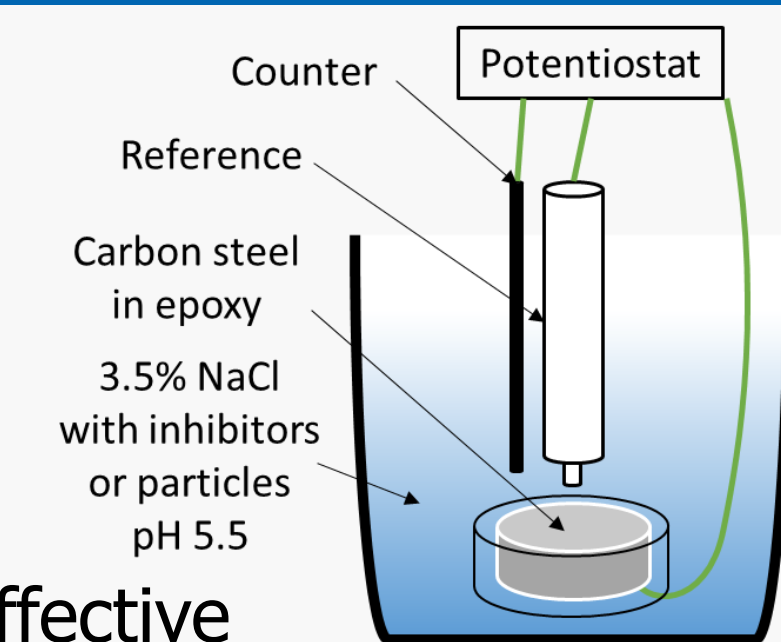


- Tunable release properties for short- and long-term corrosion protection
- Analysis of particle payload & release properties guide formula changes
- Improved formula: Doubling of inhibitor content and release amounts

## Corrosion Testing: Polarization

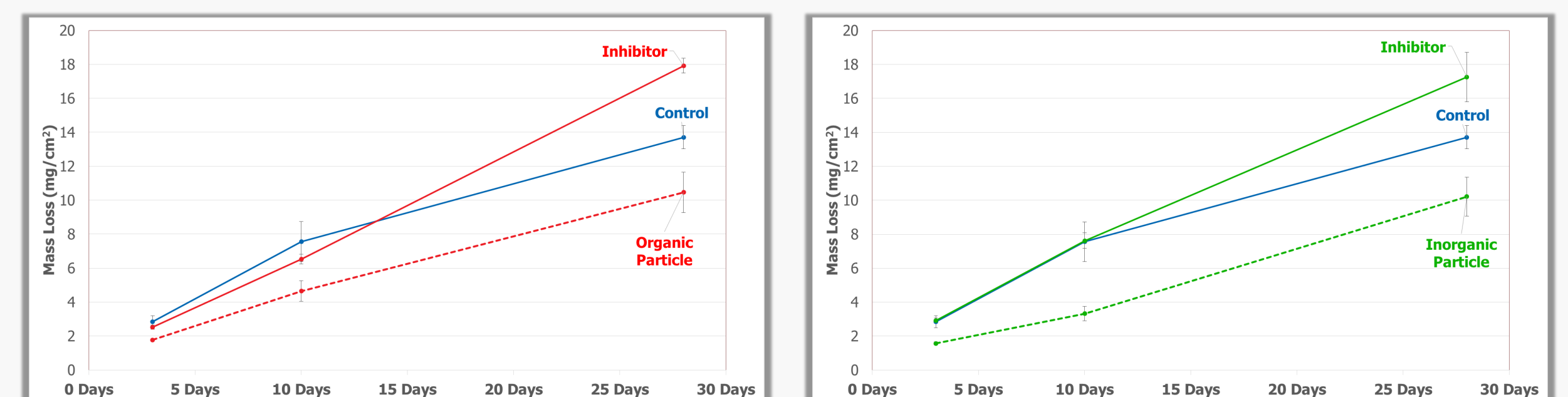
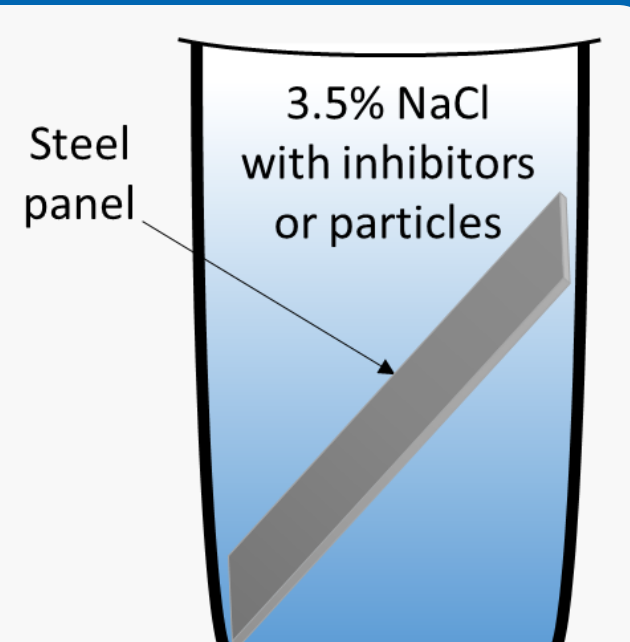
Inhibitors or particles in solutions result in:

- Increases in corrosion potential
- Shifts in anodic & cathodic curves  
→ Inhibitors significantly reduce corrosion  
→ Microparticles show same inhibition: just as effective



## Corrosion Testing: Mass Loss

- Inhibitors: same/worse corrosion rate than control
- Particles: reduce corrosion rate over 4 weeks  
→ Outperform pure inhibitors  
→ Targeted delivery of inhibitor to corrosion sites  
→ Improved corrosion protection



## Conclusion

- Encapsulation of organic and inorganic corrosion inhibitors into organic and inorganic delivery systems
- Corrosion triggered release observed
- Tunable release properties for short- and long-term protection
- Study of release properties leads to higher payloads and release amounts
- Corrosion inhibition of microparticles meets or exceeds that of pure inhibitors
- Coating compatible microparticles provide superior corrosion protection

## Future Work

- Assess release property efficacy in coating systems and for other metals
- Determine corrosion inhibition efficiency of other promising inhibitors and microparticles
- Test suitability of inhibitors and delivery systems for other metals (e.g. Aluminum)
- Study coating compatibility issues
- Characterize using other corrosion tests, e.g. salt spray & atmospheric exposure
- Shelf-life determination
- Adaptation to other NASA applications

Carbon Steel; Waterborne Acrylic Coating; Salt Spray; 790 hours

